18

A methodological toolkit for studying human-AI interaction

Sonsoles López-Pernas 0000-0002-9621-1392, Kamila Misiejuk 0000-0003-0761-8703, Eduardo Oliveira 0000-0001-5063-8860, and Mohammed Saqr 0000-0001-5881-3109

Abstract: Human-Artificial Intelligence Interaction (HAI) has evolved from static tool usage into a dynamic, co-adaptive partnership. However, dominant empirical paradigms frequently prioritize benchmarking AI outputs over modeling the interaction process itself. To address this methodological gap, this chapter introduces Dynalytics, an overarching framework and methodological ecosystem designed for the rigorous structural and temporal analysis of dynamic systems, which we apply to HAI. We demonstrate how three core network modalities—Transition Network Analysis, Heterogeneous Transition Network Analysis, and Multi-Cluster Multi-Level networks—can capture HAI across varying dimensions of relational and structural granularity. Using an empirical dataset of undergraduate students interacting with ChatGPT during a programming assignment, we showcase how these methods reveal behavioral feedback loops, role enactments, and self-regulated learning macro-phases. Moreover, the framework integrates a multi-level confirmatory testing battery—including bootstrapping, permutation testing, and centrality stability—to transition process-oriented HAI research from purely descriptive visualizations to robust statistical inference.

Keywords: artificial intelligence; Dynalytics, transition network analysis; sequence analysis; large language models; human-AI interaction

Introduction and Background

Human-Artificial Intelligence Interaction (HAI) is an emerging field of inquiry that is shaped by the evolving capabilities of artificial intelligence (AI) systems and the ways humans adapt to and integrate these technologies into their lives (Sun et al., 2023). With the rapid rise in the adoption of generative AI tools such as ChatGPT, HAI is becoming increasingly integral to many professional activities, such as writing (Steiss et al., 2024), software development (Liu et al., 2023), and medical diagnosis (Zhang et al., 2024). Humans no longer treat AI as a mere tool that can be used to facilitate their tasks, but rather as an interactive partner that influences how problems are approached, how solutions are developed, and how decisions are made. Despite the growing partnership between humans and AI, much of the current research focuses on its outputs and capabilities (e.g., benchmarking studies) (Eriksson et al., 2025), or how AI impacts human functioning. The dynamic nature of the interaction itself, i.e., the process, is often overlooked. We argue that understanding HAI as an interactive and dynamic process is essential for understanding how AI impacts humans, and how humans change with AI, as well as the dynamics of this collaboration (Rinja et al., 2027; López-Pernas et al., 2025; Saqr, Misiejuk, et al., 2026). Accordingly, we need to study how both humans and AI adapt, learn, and co-create in real time, emphasizing mutual influence and collaboration (López-Pernas, Misiejuk, Kaliisa, et al., 2025).

To fully understand HAI, it should be studied as a bidirectional and evolving process, where both humans and AI adjust to each other's behaviours. AI is not a static tool, and therefore, research should explore how humans make sense of and engage with AI-generated outputs, how emotions and social cues influence the interaction, and how collaboration and co-creation unfold in real time. An example of the dynamic nature of HAI is illustrated by Rinja et al. (2026), who found that users' interaction strategies influenced the role assumed by the AI: high-performing participants engaged in exploratory, inquiry-driven exchanges that elicited tutor-like responses, whereas lower-performing participants more often delegated tasks, leading the AI to adopt an executor role that primarily provided ready-made solutions. The present chapter aims to address this issue by offering a methodological framework for capturing the dynamics of HAI with emphasis on both the relational and temporal

dimensions. First, we study how AI systems respond to human feedback and how shared understanding emerges to uncover the subtle, often overlooked mechanisms that shape effective interaction and cooperation.

Second, a process-oriented approach is necessary for advancing AI alignment and congruence with human values to ensure that we capture the negotiated process of alignment that unfolds through interaction (Anwar et al., 2024; Ji et al., 2023). More importantly, it helps explain how and when events happen, what they precede, and how they lead to outcomes. A process perspective enables us to explore how alignment is sustained, challenged, or recalibrated in response to new contexts, shifting goals, or evolving user needs—offering a more robust and realistic understanding of what it means for AI to remain aligned over time.

Finally, emphasizing the interaction process broadens our conceptualization of intelligence and design. It encourages us to move beyond viewing AI as an isolated performer and capture the human-AI co-adaptive, collaborative, and co-evolutive system. This shift reframes our design goals to create human-AI systems that are collaborative, resilient, and capable of enhancing human agency and decision-making. It recognizes that the value of AI lies in how it engages with and changes alongside the people who use it, as well as maps and traces such processes (Saqr, Misiejuk, et al., 2026).

Scholars have also recently called for this shift toward process-oriented and socially-situated views, where AI is a part of a broader system of cognition and communication. For example, Cabitza et al. (2021) argue that AI should be understood as a "knowledge artifact"—a mediating structure embedded within collective decision-making. Similarly, Ziegler and Donkers (2024) propose rethinking HAI from a dialogic lens, in which understanding is co-constructed over time through iterative exchanges. We concur with such perspectives in that collaboration with AI goes beyond the outcome produced to how users engage, reflect, and adapt within HAI. However, empirical methods capable of modeling this temporal and structural complexity remain scarce, which is the gap we aim to fill in the present chapter.

Dynalytics

The dynamics of HAI are relational, temporal, multifaceted, and complex, and therefore necessitate a comprehensive framework that captures the full breadth of the process. More importantly, it requires a rigorous framework that allows us to make evidence-based and verifiable claims about research conclusions. In this chapter, we draw on Dynalytics, an overarching framework and methodological ecosystem designed for the analysis and rigorous validation of dynamical systems (Saqr, López-Pernas, et al., 2026). HAI fits the archetype of a complex dynamical system, exhibiting some of its emblematic characteristics such as hierarchy, nonlinearity, feedback loops, and emergence. As such, Dynalytics offers a suitable methodological framework for the study of HAI. Dynalytics encompasses transition network analysis (TNA) and a diverse family of models and statistical methods that use a unified approach of scientific rigor and a consistent confirmatory testing battery. We describe in this section each of the main layers of Dynalytics and how we operationalize them for HAI.

1) **Data.** Dynalytics as a framework supports a wide variety of data types that represent dynamical systems, including tabular data, ecological momentary assessment data, and —most commonly— event logs. Recent advances in AI have made HAI dominated by conversational interactions that are better captured by a timestamped event log of prompts and responses, where each exchange is qualitatively coded to reflect intent, role, strategy, sentiment, or other constructs under study (Deriba et al., 2026). The analysis of event log data has been a dominant approach in neighboring fields such as learning analytics or game analytics.
2) **Estimation methods.** Networks are the signature method for representing and analysing complex dynamic data in Dynalytics. How networks are computed from the data is highly dependent on the dataset itself, but also on the research question or goal at hand. Dynalytics takes TNA as a departure point, where nodes are events and edges are transition probabilities between events, considering that an event depends

only on the immediately previous event (i.e., Markov property) (Saqr et al., 2025). This operationalization of the edges is generally appropriate for HAI interactions, as the turn-based prompt-reply dynamic lends itself naturally to modeling local transitions between actions. When the amount of data is not sufficient for inference, frequency TNA (where edges represent transition counts rather than probabilities) might be more appropriate. Dynalytics also supports longer-memory processes, such as attention TNA (López Pernas et al., 2026a), where transitions that span more than a single step are taken into account with smaller weights, offering a useful extension when capturing broader sequential dependencies across the interaction. When temporal data or the direct order of codes is not available (or not useful), Dynalytics supports co-occurrence networks where edges represent whether each pair of events is present within the same unit of analysis (e.g., a conversation or a project). The interactions between humans and AI—which are represented as the nodes in the network— may be part of a flat taxonomy structure where all nodes are at the same level or, in turn, they can belong to a more complex structure; for example, be part of a hierarchical taxonomy, or certain nodes might be associated with different types of actors (humans vs. AI). In such cases, higher-order networks can aid in representing such complex interdependencies within the data. We elaborate further on how these higher-order networks can be used for modeling HAI in the example case study in the next section.

3) **Confirmatory testing**. Dynalytics relies on a multi-level confirmatory testing battery (Saqr, López-Pernas, et al., 2026) to validate the supported models as well as to support any analytical claim: split-half reliability for internal consistency, bootstrapping for edge-level stability, case dropping for centrality stability, and permutation-based group comparisons. Such a confirmatory layer enables going beyond a descriptive approach to analyzing process data and enables statistical inference, which allows for substantiating claims and generalizing findings. For instance, bootstrapping allows identifying consistent transitions between events in HAI processes that are likely to replicate and generalize. Permutation testing enables transition-level group comparison between, for instance, control and experimental groups, or different cohorts.
4) **Analytical layer**. The combination of networks as the analytical backbone and process analysis leverages the full potential of both methods. As such, in addition to networks as a tool for visualizing high-dimensional data, centrality measures allow us to identify central events to the process, and community finding allows us to group events together that are closely connected to one another (Saqr, López-Pernas, et al., 2026). Sequence analysis allows for mapping the longitudinal unfolding of the process from beginning to end, and sequence pattern mining enables the identification of recurring event patterns.
5) **Software packages**. To support all layers of analysis, Dynalytics relies on a comprehensive software suite. The *Nestimate* package provides the network estimation methods earlier discussed (Saqr & López-Pernas, 2026b). The *cograph* package provides visualization and network-related operations (Saqr & López-Pernas, 2026a). The *codyna* package provides methods to study process dynamics (Tikka et al., 2026). The *tna* (Tikka et al., 2025) and *htna* (López-Pernas et al., 2026c) packages provide specialized wrappers for TNA and Heterogeneous TNA (HTNA) specifically. Graphical interfaces such as the Dynalytics web app and JTNA (for Jamovi) are available as well.

Example case study

Throughout the remainder of this chapter, we exemplify the Dynalytics framework using three distinct methods: TNA, HTNA, and Multi-Cluster Multi-Level (MCML) to reveal different aspects of HAI. We use data collected from undergraduate students' conversations

with ChatGPT during a programming assignment in a real classroom setting (López-Pernas, Misiejuk, Oliveira, et al., 2025). Students were allowed to use ChatGPT freely throughout the task, and their interactions with the tool were collected using the *chatgptscrapeR* (López-Pernas, Misiejuk, Jovanović, et al., 2025) R package to better understand how AI supports learning and problem-solving. The final dataset included interactions from 93 students and over 2,000 exchanges with ChatGPT.

We qualitatively coded students' prompts and AI responses using different codebooks, each with a different analytical lens in mind (see Table 1). For the TNA analysis, we chose a codebook in which the students' responses are coded according to their problem-solving and SRL actions, while all AI responses were only coded as "*AI"*. As such, the analysis focuses on modeling the student side of interactions. As HTNA enables the use of two classes of nodes to model AI and student interactions at the same time, student prompts and AI responses were coded in accordance with the role they enact in the problem-solving process. Finally, the MCML analysis captures events both across and within phases and/or constructs. In our example, we follow the hierarchy established in Prasad & Sane's framework (2024), which divides the process into three clusters: *Problem Understanding*, *Solution Evaluation*, and *Self-regulation* to capture the content of students' prompts. The data and code needed to replicate the analysis are available as Supplementary Material.

Table 1. Frequencies of the codes used in TNA, HTNA, and MCML analyses divided by the actor type.

Actor type	TNA	HTNA	MCML
Human	**Adapt** (n = 492, 22.09%) **Affect** (n = 25, 1.12%) **Context** (n = 82, 3.68%) **Evaluate** (n = 34, 1.53%) **Explain** (n = 5, 0.22%) **Iteration** (n = 212, 9.52%) **Monitoring** (n = 231, 10.37%) **Planning** (n = 48, 2.16%) **Reflection** (n = 23, 1.03%) **Specification** (n = 195, 8.76%)	**Debug** (n = 266, 13.27%) **Inquire** (n = 97, 4.84%) **Instruct** (n = 429, 21.4%) **Seek.Help** (n = 93, 4.64%) **Socialize** (n = 37, 1.85%)	**Problem** (n = 489) **Specification** (n = 195, 14.48%) **Context** (n = 82, 6.09%) **Iteration** (n = 212, 15.74%) **Solution** (n = 526) **Inspect/Adapt** (n = 477, 35.41%) **Decompose** (n = 15, 1.11%) **Explain** (n = 34, 2.52%) **SRL** (n = 332) **Monitoring** (n = 231, 17.15%) **Planning** (n = 48, 3.56%) **Affect** (n = 25, 1.86%) **Explanation** (n = 5, 0.37%) **Reflection** (n = 23, 1.71%)
AI	**AI** (n = 880, 39.52%)	**Analyzer** (n = 38, 1.9%) **Coder** (n = 184, 9.18%) **Supporter** (n = 593, 29.58%) **Sycophant** (n = 13, 0.65%) **Tutor** (n = 255, 12.72%)	-

Transition Network Analysis

TNA models events and states within a single flat alphabet, whereby no hierarchical or categorical assumptions or distinctions are made between them at the analytical level (see Fig. 18.1a). These are then represented as nodes in a network, with the edges connecting them signifying transition probabilities. Dynalytics's confirmatory testing allows us to evaluate whether observed transition structures differ significantly from chance. For instance, bootstrapping procedures can be applied to estimate the stability and confidence intervals of transition probabilities (blue transitions in Fig. 18.1a).

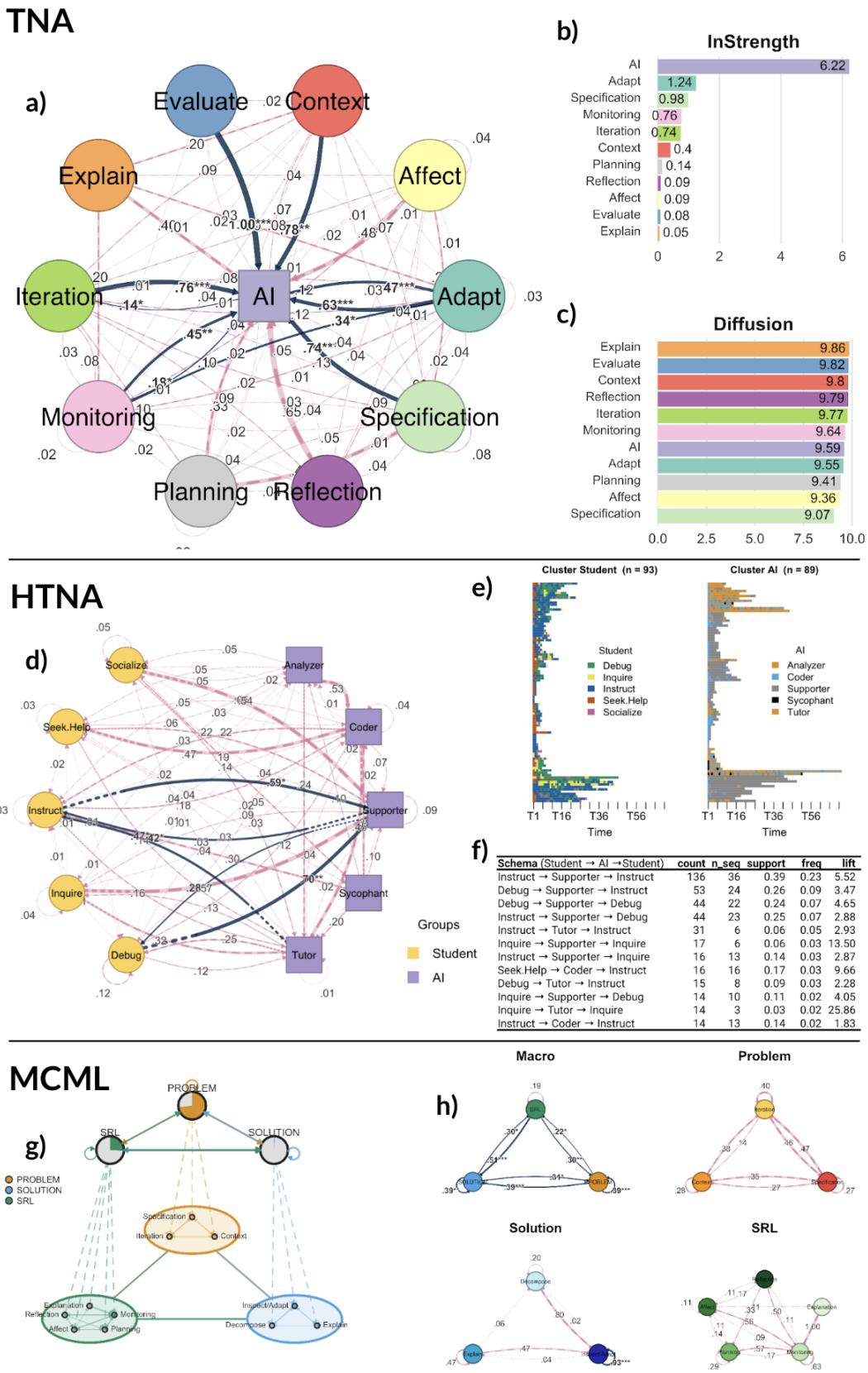


Figure 18.1 Three analysis lenses. TNA: a) Bootstrapped transition network estimated with TNA. In-strength (b) and diffusion centrality (c). HTNA: Bootstrapped transition network estimated with HTNA where nodes represent events enacted by students (yellow) or AI (purple) (d); Sequence index plot per actor type (e); Top 10 meta paths for the Student → AI → Student schema (f). MCML: MCML network (g) and individual macro and micro level networks (h)

At the analytical layer, visualizing the process as a network allows for the identification of structural patterns, recurrent pathways, and relational dependencies within the sequence. Combining both enables making observations about the process that are supported by empirical evidence. For instance, Fig. 18.1a shows a recurring loop between *solution adaptation*, *iterative conversation*, and *process monitoring* with *AI* use, whereas transitions between different codes in the same prompt are scarce and non-significant. Centrality measures help quantify the role of each node in the network, with solution *adaptation* and problem *specification* having the highest in-strength (receiving more transitions, besides AI responses, of course) (Fig. 18.1b). *Explain*, *evaluate*, and *context* have the highest diffusion centralities (Fig. 18.1c). However, a centrality stability test based on case dropping reveals that in-strength has a high centrality stability coefficient (0.9), whereas diffusion has a lower one (0.5), which implies that it is not a reliable measure to draw conclusions from.

Heterogeneous Transition Network Analysis
HTNA (López-Pernas et al., 2026b) makes an explicit distinction between actor types, where events are exclusive to each specific actor. In the case of HAI, certain events would only be operationalized by the human and others by the AI, with no overlap between them. Such a distinction is not merely visual but rather embedded within the model estimation and analytical layers. Fig. 18.1d shows the bootstrapped transition network for the roles (the nodes in the network), where there is a clear feedback loop between *Instruct* and *Supporter*, and between *Debug* and *Supporter*. The sequence index plot (Fig. 18.1e) shows the longitudinal unfolding of the process for each actor type, highlighting, for instance, the persistence of the *Supporter* role, especially in longer sequences. The mapping between actor types and nodes is embedded in the analytical layer and transcends mere visualization. For example, meta paths can detect sequential patterns that follow a specific schema, such as alternating between human-initiated actions and AI responses (see Fig. 18.1f). The most frequent such three-step meta path identified in our dataset was a student submitting a coding request to ask the AI to generate new code, add a feature, or fix an existing issue (*Instruct*), the AI then providing feedback or assistance in response (*Supporter*), and the student subsequently submitting another coding request of the same nature (*Instruct*). From a purely frequentist approach, we can only ascertain that *Instruct* and *Supporter* are the most enacted codes, but not how they are intertwined and how they temporally relate to other codes.

Multi-Cluster Multi-Level
MCML networks cluster codes into higher-level categories and render TNA networks at both levels: summary edges between clusters show the macro-level TNA; internal edges show micro-dynamics within each cluster (see Fig. 18.1g). The pie-like chart shows the proportion of outgoing transitions from each node that remain within its own cluster (colored slice) versus those that flow to nodes in other clusters (gray slice). In our example, the *Problem* macro-cluster has the most outgoing transitions. Both the analytical and the confirmatory layers of Dynalytics can be applied to both the intra-cluster network (formed by the event subtypes within each chapter) and to the inter-cluster network (transitions between clusters). Fig. 18.1h shows the bootstrapped networks at the macro and micro levels (three separate networks). Transitions are only statistically significant at the macro-level with the exception of *Inspect/Adapt*, which has a significant self-loop (recurrent action). Other confirmatory tests can be performed at either level, and so can all the analytical operations encompassed within Dynalytics (centralities, communities, cliques, etc.).

Discussion

In this chapter, we have described how the Dynalytics framework can be operationalized for modeling HAI as a complex dynamic system from a process-oriented lens, studying its dynamics and validating findings with confirmatory testing. Specifically, we showcase how

TNA, HTNA, and MCML can be used to model the HAI process through different analytical lenses and at different levels of granularity. HTNA is appropriate when there are clear actor types, each with its own events, and we are interested in studying complex relationships and patterns between such actor types. MCML is appropriate when there is a nestedness in the event types that grants modeling at both levels. TNA offers the simplest approach, where all events interact at the same level. All three approaches capture both the relational and temporal dimensions of HAI. Regardless of the approach, Markov models are suitable for modeling short-memory processes where the probability of transitioning to a new state depends only on the previous state. As such, they are aligned with the stochastic nature of HAI, especially with LLMs, which work with short windows and limited memory. In addition to this, Dynalytics introduces several validation techniques that allow researchers to verify their findings and remove negligible patterns. This work thus positions HAI research within the broader tradition of studying complex adaptive systems, where understanding emerges not from optimal endpoints but from the evolving patterns of interaction among components across time (e.g., Holland, 1992). Capturing these patterns with rigor and granularity is not merely a methodological choice but a scientific necessity.

Supplementary Material
Code and data: https://doi.org/10.6084/m9.figshare.32896808

Funding acknowledgement
This research has been conducted with co-funding from the Research Council of Finland through the project CRETIC (Decision 360746) and from the Stiftung Innovation in der Hochschullehre through the LEAD:FUH project (1001-3223).

References

Anwar, U., Saparov, A., Rando, J., Paleka, D., Turpin, M., Hase, P., Lubana, E. S., Jenner, E., Casper, S., Sourbut, O., Edelman, B. L., Zhang, Z., Günther, M., Korinek, A., Hernandez-Orallo, J., Hammond, L., Bigelow, E., Pan, A., Langosco, L., … Krueger, D. (2024). Foundational challenges in assuring alignment and safety of large language models. In *arXiv [cs.LG]*. arXiv. http://arxiv.org/abs/2404.09932

Cabitza, F., Campagner, A., & Simone, C. (2021). The need to move away from agential-AI: Empirical investigations, useful concepts and open issues. *International Journal of Human-Computer Studies*, *155*(102696), 102696. https://doi.org/10.1016/j.ijhcs.2021.102696

Deriba, F., López Pernas, S., Misiejuk, K., & Saqr, M. (2026). *Analytics of the human-AI interaction process: A systematic literature review*. https://doi.org/10.2139/ssrn.6067612

Eriksson, M., Purificato, E., Noroozian, A., Vinagre, J., Chaslot, G., Gomez, E., & Fernandez-Llorca, D. (2025). Can we trust AI benchmarks? An interdisciplinary review of current issues in AI evaluation. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*, *8*(1), 850–864. https://doi.org/10.1609/aies.v8i1.36595

Holland, J. H. (1992). Complex Adaptive Systems. *Daedalus*, *121*(1), 17–30. https://www.jstor.org/stable/20025416

Ji, J., Qiu, T., Chen, B., Zhang, B., Lou, H., Wang, K., Duan, Y., He, Z., Vierling, L., Hong, D., Zhou, J., Zhang, Z., Zeng, F., Dai, J., Pan, X., Ng, K. Y., O'Gara, A., Xu, H., Tse, B., … Gao, W. (2023). AI alignment: A comprehensive survey. In *arXiv [cs.AI]*. arXiv. http://arxiv.org/abs/2310.19852

Liu, J., Xia, C., Wang, Y., & Zhang, L. (2023). Is your code generated by ChatGPT really correct? Rigorous evaluation of Large Language Models for code generation. *Neural Information Processing Systems*, *abs/2305.01210*, 21558–21572. https://proceedings.neurips.cc/paper_files/paper/2023/hash/43e9d647ccd3e4b7b5baab53f0368686-Abstract-Conference.html

López-Pernas, S., Misiejuk, K., Jovanović, J., Raspopović Milić, M., Conde, M. Á., & Saqr, M. (2025). chatgptscrapeR: A Tool for Retrieving Student-AI Interactions. *Proceedings of the 2025 International Conference on Advanced Learning Technologies (ICALT)*, 134–136. https://doi.org/10.1109/ICALT64023.2025.00044

López-Pernas, S., Misiejuk, K., Kaliisa, R., & Saqr, M. (2025). Capturing the process of students' AI interactions when creating and learning complex network structures. *IEEE Transactions on Learning Technologies*, *18*, 556–568. https://doi.org/10.1109/tlt.2025.3568599

López-Pernas, S., Misiejuk, K., Oliveira, E., & Saqr, M. (2025). The dynamics of the self-regulation process in student-AI interactions: The case of problem-solving in programming education. *Proceedings of the 25th Koli Calling International Conference on Computing Education Research*, 1–12. https://doi.org/10.1145/3769994.3770043

López Pernas, S., Tikka, S., Misiejuk, K., Oliveira, E., & Saqr, M. (2026a). Modeling the dynamics and impact of human-AI interactions with Attention Transition Network Analysis. In *Social Science Research Network*. https://doi.org/10.2139/ssrn.6187958

López-Pernas, S., Misiejuk, K., Tikka, S., & Saqr, M. (2026b). Role Dynamics in Student–AI Collaboration: A Heterogeneous Transition Network Analysis Approach. *Innovations in Analytics of Learning Dynamics: Proceedings of the 1st Workshop on Transition Network Analysis (TNA)*.

Heterogeneous Transition Network Analysis [R package htna version 0.1.0]. (2026). Comprehensive R Archive Network (CRAN). https://CRAN.R-project.org/package=htna

Rinja, D., Oliveira, E. A., López-Pernas, S., Saqr, M., Specht, M., & Misiejuk, K. (2027). Unpacking vibe coding: Help-seeking processes in student-AI interactions while programming. In *Artificial Intelligence in Education. AIED 2026. Lecture Notes in Computer Science* (pp. 515–530). Springer Nature Switzerland.

Saqr, M., & López-Pernas, S. (2026a). cograph: Analysis and Visualization of Complex Networks (Version 2.3.6). In *CRAN: Contributed Packages*. The R Foundation. https://doi.org/10.32614/cran.package.cograph

Saqr, M., & López-Pernas, S. (2026b). Nestimate: Network estimation, bootstrap, and higher-order analysis (Version 0.7.7). In *CRAN: Contributed Packages*. The R Foundation. https://doi.org/10.32614/cran.package.nestimate

Saqr, M., López-Pernas, S., & Misiejuk, K. (2026). Dynalytics: The Birth of a Framework for Rigorous Analytics of Dynamical Systems. In *Innovations in Analytics of Learning Dynamics: Proceedings of the 1st Workshop on Transition Network Analysis (TNA)*.

Saqr, M., López-Pernas, S., Törmänen, T., Kaliisa, R., Misiejuk, K., & Tikka, S. (2025). Transition network analysis: A novel framework for modeling, visualizing, and identifying the temporal patterns of learners and learning processes. *Proceedings of the 15th International Learning Analytics and Knowledge Conference*, 351–361. https://doi.org/10.1145/3706468.3706513

Saqr, M., Misiejuk, K., & López-Pernas, S. (2026). Human-AI collaboration or obedient and often clueless AI in instruct, serve, repeat dynamics? *The Internet and Higher Education*, *70*(101087), 101087. https://doi.org/10.1016/j.iheduc.2026.101087

Steiss, J., Tate, T., Graham, S., Cruz, J., Hebert, M., Wang, J., Moon, Y., Tseng, W., Warschauer, M., & Olson, C. B. (2024). Comparing the quality of human and ChatGPT feedback of students' writing. *Learning and Instruction*, *91*(101894), 101894. https://doi.org/10.1016/j.learninstruc.2024.101894

Sun, Y., Shen, X.-L., & Zhang, K. Z. K. (2023). Human-AI interaction. *Data and Information Management*, *7*(3), 100048. https://doi.org/10.1016/j.dim.2023.100048

Tikka, S., López-Pernas, S., & Saqr, M. (2025). tna: An R Package for Transition Network Analysis. *Applied Psychological Measurement*. https://doi.org/10.1177/01466216251348840

Tikka, S., López-Pernas, S., & Saqr, M. (2026). Analyzing Complex Dynamic Systems with

the R package codyna. In *Social Science Research Network*. https://papers.ssrn.com/abstract=6069249

Zhang, X., Talukdar, N., Vemulapalli, S., Ahn, S., Wang, J., Meng, H., Bin Murtaza, S. M., Leshchiner, D., Dave, A. A., Joseph, D. F., Witteveen-Lane, M., Chesla, D., Zhou, J., & Chen, B. (2024). Comparison of prompt engineering and fine-tuning strategies in large language models in the classification of clinical notes. *AMIA Summits on Translational Science Proceedings AMIA Summit on Translational Science*, *2024*, 478–487. https://pmc.ncbi.nlm.nih.gov/articles/PMC11141826/

Ziegler, J., & Donkers, T. (2024). From explanations to human-AI co-evolution: charting trajectories towards future user-centric AI. *I-Com*, *23*(2), 263–272. https://doi.org/10.1515/icom-2024-0020